

UNIVERSITY OF PIRAEUS



DEPARTMENT OF STATISTICS AND INSURANCE SCIENCE
POSTGRADUATE PROGRAM IN ACTUARIAL SCIENCE AND
RISK MANAGEMENT

**THE USE OF CREDIT SCORING SYSTEMS IN
MEASURING CREDIBILITY – THE CASE OF
GREEK COMPANIES**

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MSc Dissertation

Submitted to the Department of Statistics and Insurance Science of the University of Piraeus in partial fulfilment of the requirements for the degree of Master of Science in Actuarial Science and Risk Management.

Piraeus, Greece
April 2015

Acknowledgements

I would like to thank my supervisor Prof. Michael Glezakos for his guidance, kindness and especially for his patience. I appreciate his availability and rapid replies and comments to all of my work. His advice has clearly impacted on the quality of this thesis. I would, also, like to thank my classmates with whom I cooperate during those 2 school years. Finally, I would like to express my gratitude to all my professors who gave me all this necessary knowledge being able to cope with in such a competitive environment.

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Abstract

Credit risk is crucial for all companies and privates. It was obvious especially in period of 2008-2010, when many developed economies experienced a recession, due to financial crisis.

In the relevant literature, among the suggested methodologies to measure and manage this kind of risk, credit scoring models are included. They usually utilize accounting data, which convey crucial information about vital functions of a company.

In the current study, we tried to record the most popular methodologies as well as to indirectly test the relevance of liquidity, profitability and capital structure to credit risk. More particularly, given that liquid, profitable and properly funded companies convey less credit, we assumed that such companies should exhibit a satisfactory performance. We assumed therefore, that liquidity, profitability and capital structure should be strongly related to a company's common return.

Analyzing the data of 80 companies, listed in the Athens Stock Exchange, we concluded that the above assumption didn't hold, at least for the period under study (2000-2007).

Chapter 1

Purpose of the Study

The purpose of this empirical study is to create a new credit rating system which measures the trustworthiness of consumers and financial institutions. In other words, it estimates the consumer's probability to not fulfill his economical obligations on lenders, giving him a rating point. Depending this point, every borrower can be ranked on the rating system and be clearly about his creditworthiness ability.

The first chapter gives to readers an extended analysis to what exactly credit risk is and the parameters of it. It is, also, represented the meaning and the goal of credit scores as well many logical questions, which are made during all these years, are answered by the economic experts. There is, also, an analysis about the Basel Committee and all the frames from 1974 to 2019. Finally, there is a report about the credit scores that are used by different countries all over the world.

The second chapter explains why scorecards are mentioned as a way of credit measurement and they have been categorized and analyzed according to the different types. Moreover, there is an extensive historic analysis for each statistical techniques which are used in order to minimize the credit risk.

In the third chapter, a statistical model has been created in order to make a new rating system. All the data was given by the Athens Stock Exchange. A sample of companies was selected randomly. After that, it is validated using economic ratios and the financial theory.

In the fourth chapter, characteristics that are used to statistic analysis, are being mentioned as a very important tool to describe the distribution of data. They are examined methodically and in detail. Also, many charts have been used to compare and analyze the relation between the ratios and the returns of stocks.

The last chapter presents a summary of this thesis by marking the most important issues. Finally, there is an explanation for the reason why there was not any chance to make a new rating system.

CHAPTER 2

The Theoretical Framework of Credit Risk

1. Introduction to Credit Risk

Credit risk is the risk of loss of principal or loss of a financial reward stemming from a borrower's failure to repay a loan or otherwise meet a contractual obligation. It arises whenever a borrower is expecting to use future cash flows to pay a current debt. If there is a credit risk, investors are compensated by ways like interest payments from the borrower or issuer of the debt obligation. In other words, credit risk occurs when a borrower is not able to fulfill his contractual obligation.

It is certain that, the higher the perceived credit risk, the higher the rate of interest that investors will demand for lending their capital. Credit risk calculation is based on the borrowers' overall ability to repay (collateral assets, revenue – generating ability and taxing authority). Credit risk can affect many components of a bank such as loans, bond, inter – bank transactions and derivatives. It is, also, a vital component of fixed – income investing. That is why ratings agencies such as S&P, Moody's and Fitch evaluate the credit risks of thousands of corporate issuers and municipalities on an ongoing basis.

The three major characteristics of credit risk are the probability of default (PD), the exposure at default (EAD) and the loss given default (LGD).

1.1 Expected Loss (EL)

In statistical terms, the expected loss (EL) is the average credit loss that one would expect from an exposure or a portfolio over a given period of time.

The expected loss is measured using the following formula:

$$EL = PD \times EAD \times LGD$$

The total expected loss of a portfolio is simply be the total amount of expected losses of individual assets. Usually, business corporations have budget for the expected losses, since they are what a business expects to lose in a year. The losses can be borne as a part of the normal operating cash flows.

1.2 Unexpected Loss (UL)

The unexpected loss (UL) is the average total loss over and above the mean loss. It is calculated as the standard deviation from the mean at a certain confidence level. It is also known as Credit VaR. A corporation can reduce unexpected losses by allocating capital employed in various activities (diversification effect).

The unexpected loss of a portfolio at a 99% confidence level will be expressed as follows:

$$UL = D99\% - EL$$

Where: D99% represents the 99% Var quartile.

1.3 Probability of Default (PD)

Probability of default (PD) is the likelihood that the borrower of a loan or debt will be unable to make the necessary scheduled repayments. If it finally happens, the lenders can only attempt to obtain at least partial repayment. Generally speaking, the higher the probability of default of a borrower, the higher the interest rate the lender will charge the borrower as compensation for bearing higher default risk.

Under Basel II, a default event on a debt obligation can be occurred if:

- the obligor will not be able to repay an unsecured debt
- the obligor is more than 90 days past due on a material credit obligation.

The PD is an estimation of the likelihood that the default event will occur over a fixed assessment horizon, usually taken to be one year. It can be estimated for a particular obligor (wholesale banking), or for a segment of obligors sharing similar credit risk characteristics (retail banking). The PD does not only depend on the risk characteristics of that particular obligor but also the economic environment and the degree to which it affects the obligor. Thus, the information which is helpful to estimate PD can be divided into two broad categories:

- Macroeconomic information like house price indices, unemployment, GDP growth rates, etc. This information remains the same for multiple obligors.
- Specific information like revenue growth (wholesale), number of times delinquent in the past six months (retail), etc. This information refers to a single obligor and can be either static or dynamic in nature.

An unstressed PD estimates when the obligor default over a particular time horizon considering the current macroeconomic as well as the specific information. This implies to contrary situations, if the macroeconomic conditions deteriorate, the PD of an obligor will tend to increase while it will tend to decrease if economic conditions improve.

On the other hand, a stressed PD estimates when the obligor default over a particular time horizon considering the current obligor specific information, also considering "stressed" macroeconomic factors irrespective of the current state of the economy. The stressed PD changes over time depending on the risk characteristics of the obligor, it is not heavily affected by changes in the economic cycle as adverse economic conditions are already factored into the estimation.

There are many ways of estimating the probability of default. Firstly, a historical data base of actual defaults using modern techniques like logistic regression could achieve the specific goal. It may also be estimated from the observable prices of credit default swaps, bonds, and options on common stock. Although, the simplest approach is to use external ratings agencies such as Standard and Poors, Fitch or Moody's Investors Service concerning the historical default experience. For small business, logistic regression is the most common technique based on a historical data base of defaults

for that specific estimation. These models are both developed internally and supplied by third parties. A similar approach is taken to retail default, using the term "credit score".

1.4 Exposure at Default (EAD)

Exposure at default is a total value that a company is exposed to at the time of default. Each exposure gives to company an EAD value and it is identified within the bank's internal system. Using the internal ratings board (IRB) approach, financial institutions will often use their own risk management default models to calculate their respective EAD systems. Calculation of EAD by applying foundation or advanced approaches, produces different results. Under foundation approach (F-IRB) it is guided by the regulators, while under the advanced approach (A-IRB), institutions enjoy greater flexibility on the calculation. The expected loss is often measured over one year. Usually it is calculated by multiplying each credit obligation by an appropriate percentage. Each percentage used coincides with the specifics of each respective credit obligation. Any error in EAD calculation directly affect the value of risk weighted asset and thereby affects the capital requirement.

1.5 Loss Given Default (LGD)

Loss given default is the amount of funds that is lost by a financial institution when a borrower defaults on a loan. Through the analysis of the actual loan defaults, companies will determine their credit losses. Quantifying losses is not always simple. In some circumstances it is quite difficult and requires the analysis of many variables. The process of analyzing all of these variables is of paramount importance to determine the loss given default.

Theoretically, LGD is calculated in many ways. The most popular is 'Gross' LGD method, according to which total losses are divided by exposure at default (EAD). Another method is to divide losses by the unsecured portion of a credit line, known as 'Blanco' LGD. If collateral value is zero then Blanco LGD is equivalent to Gross LGD. Academics suggest several methods for calculating the LGD, but the most frequently used method compares actual total losses to the total potential exposure at the time of default. Most companies do not simply calculate the LGD for one loan.

They review their entire portfolio and determine LGD based on cumulative losses and exposure.

2. Capital Adequacy

As we referred previously, credit risk is possible to occur when an individual borrower or a financial institution is incapable to repay its contractual obligations. So, every lending system has to be able to predict this, in order to save its interests.

Capital adequacy is referring to the bank's capacity to meet the time liabilities and other risks such as credit risk, operational risk etc. A bank's capital is the limit for potential losses, and protects the bank's depositors and other lenders. In case of greater losses, institution have to maintain more capital. A modern approach to predict the level of capital adequacy, is by examining the relation between the regulatory and weighted capital together to risk of assets. Every financial institution has to maintain regulatory capital equal to risk that has been taken over.

In 1974, Basel Committee on Banking Supervision was created by bankers of the most economically strong countries, all over the world, (G10) in order to come up with the problems on financial markets. The committee comprises representatives from central banks and regulatory authorities.

In 1988, Basel published a set of minimum capital requirements for banks, known as Basel I. All the members of Committee decided to use common measures, so every credit institution got sufficient capital and avoid problems of lack of it. Basel I forecast capital only in the case of credit risk (default risk), the risk of counter party failure. One of the major role of Basel norms is to standardize the banking practice across all countries. However, there are major problems with this. Accounting practices vary significantly across the G-10 countries and often produce results that differs markedly from market assessments. Another problem was that the risk accounts do not attempt to take into account the other kind of risks like market risk, operational risk etc., but only the credit risk.

So, in 2004, it was presented a new set of rules known as Basel II which was an extended form of Basel I. This new frame, reviewing the way that credit institutions

measure the needed capital requirements, tried to improve the credit system making it more safely and stable. It showed guidelines for capital adequacy, risk management and disclosure requirements. More analytically, Basel II allow the use of external ratings systems to set the risk weights, market participants could assess the capital adequacy for every institution based on information of risk exposures, capital etc.

Because of the fact that, Basel II focused more in individual financial institutions, ignoring the systemic risk, a new frame, Basel III, were proposed in 2010. It is an inclusive set of measures designed to improve the regulation, supervision and generally, the risk management within the financial institutions. It was agreed to introduced from 2013 until 2015 but changes extended its force until 2019. There were more changes on the latest set performing the new Basel III. This third installment was developed in response to the deficiencies in financial regulation revealed by the financial crisis of 2008. Basel III was supposed to strengthen more bank capital requirements by increasing bank liquidity and decreasing bank leverage.

Basel III does not reconsider the measures of credit risk that Basel II have made, but it made some corrections on these. The guidelines that Basel III sets, aim to make a stronger banking system focused on capital, leverage, funding and liquidity. The requirements for equity and Tier I will be 4,5% and 6% respectively (Basel II sets equity > 8% and Tier I > 4%). In addition, the liquidity coverage ratio (LCR) will require banks to hold a buffer of high quality liquid assets sufficient to deal with the cash outflows encountered in an acute short term stress scenario as specified by supervisors. Finally, leverage ratio will be at 3%.

3. Credit Risk Management

The definition of credit risk management varies from one financial institution to the other, depending on the type of business they are into. An institution must consider the features of its target market to develop an appropriate credit strategy. They are some parameters that it has to think about such as the target market, the type of the product that will be offered, the geographical area and the legal requirements associated, the currency (euro), the pricing policy and, finally, the maturity of the market within the area.

Companies may fail to assess and manage credit risk proactively. That might be detrimental to the financial health and may lead to severe losses. The credit risk formalizes the credit risk management process of the institution and states the tolerance of the board for credit exposure. Once the risk of the institution is clearly defined, the credit policy will make clear how it plans to control credit risks within the predefined limits. The policy presents techniques and processes for avoiding, mitigating and effectively managing credit exposure to an acceptable level. The credit policy is usually revised once a year.

For years, creditors have been using credit scoring systems to determine whether a consumer is a good risk for being a borrower. More recently, credit scoring has been used to help creditors evaluate a consumer's ability to repay home mortgage loans and whether to charge deposits for utility services. It has been, also, used for auto loans and credit cards. Many auto and home insurance companies use special credit scores to decide whether to issue a policy and for how much.

3.1 Credit Scoring

A credit score is a number which characterizes a consumer, generated by the credit institutions by reviewing his past credit history. It helps the lenders in determining whether he has the financial strength to return the money within the given time period. Briefly, credit score is just a synopsis of his credit worthiness. The primary purpose of a credit score is to help lenders assess the level of risk. By other words, using credit scores has helped lenders and creditors speed up the process. This automation has helped to reduce the amount of personal review time for a credit application. A credit score is also used by some creditors to help them decide, based on consumer's credit score and the predicted level of risk, some details like interest rate and loan terms that will be offered.

Credit score is the most important feature of the credit health of a borrower. Having a good credit score is an asset and can assure of a secured financial future. On the other hand, a bad credit score will result in a higher cost when consumer needs to borrow money. The prime aim is to maintain a good credit score and lead to financially planned life. This will be easier, if any borrower is aware of the important factors that evaluate his credit worthiness.

For example, when someone applies for a loan, the credit score plays a vital role in the approval of the loan. This is because his credit score reflects his ability to repay the credit. The approval of a loan depends on an individual's credit history. This again is relevant in terms of interest rate, fees, and other charges which are usually charged and varies from one person to another. This will make any person more cautious and allow him to mend the risks before he finally applies for a loan.

It is certain that, there are several questions that any financial institution has to answer, so the system of credit scoring could be absolutely understandable.

➤ How does credit scoring work?

Credit scoring takes into account information provided directly by the consumers, any information the company may hold about them, and any information it may obtain from other organizations. This kind of information is numbers and types of accounts, collection actions, bill – paying histories, outstanding debt and the age of accounts. Each company may use information from other organizations, which may include a licensed Credit Reference Agency (we will analyze who they are upon request).

The credit scoring system allocates points for each piece of relevant information and adds these up to produce a score. When consumer's score reaches a certain level, the institution will generally agree to his application. If his score does not reach this level, application may not be approved. Sometimes scores are calculated by a Credit Reference Agency and companies may use these in their assessments. The points are based on analysis of large numbers of repayment histories over many years. This statistical analysis enables the financial institutions to identify characteristics that predict future performance. Credit scoring produces consistent decisions and it is designed to ensure all applicants are treated fairly.

Additionally, all the companies have policy rules to determine whether they will lend or they will not. For example, if they have direct evidence that a consumer has shown poor management of credit products in the past they may decline his application. Every application which is subjected to open an account or borrow money involves a certain level of repayment risk for the lender, no matter how reliable or responsible an

applicant is. This does not mean that any declined applicant is a bad payer. It simply means that based on the information available to company, it is not prepared to take the risk of any of these actions. All lenders are not obliged to accept all the applications. Each of them has different lending policies and scoring systems, so applications may be assessed differently. This means that one lender may accept the application but another may not. If the application is declined, this will not be disclosed to the Credit Reference Agency.

➤ How is a credit scoring model developed?

Any creditor selects a random sample of its customers, or a part of similar customers if their sample is not large enough. He analyzes it statistically to identify characteristics that relate to creditworthiness. Each creditor may use either the same credit scoring system for all the applicants, either different scoring models for different types of credit, or a generic model developed by a credit scoring company. Under the equal credit opportunity act, a credit scoring system may not use certain characteristics like sex, race, marital status, national origin or religion, as factors. However, companies are allowed to use age in properly designed scoring systems. Any scoring system that includes age must give equal or better treatment to elderly applicants.

➤ How reliable is the credit scoring systems?

Although a credit scoring system may seem impersonal, it can help make decisions faster, more accurately, and more impartially than individual judgment when it is properly designed. Many creditors design their systems so that in marginal cases, like scores which are not high enough to pass easily or these which are low enough to fail absolutely are referred to a credit manager who decides whether the company will accept the application. This may give the need for discussion and negotiation between the credit manager and the consumer.

On the other hand, credit scoring does have some flaws. Credit scoring is only as good as the information in the credit report and credit reports are notorious for containing errors. Credit scoring programs often cannot generate a score if the consumer has no

recent activity on an account, usually within the last six months. This can be a problem for seniors who have paid off all their loans and do not use credit cards.

➤ Which are the contents in a credit score?

First of all, a very important clue is to identify the information. This information generally contains your name, address, social security number, date of birth and employment information. For credit scoring base information are not required. It is provided by borrower to the lender. Secondly, creditors have to know the trade lines. Under this head any borrower gets access to his credit account details. This may include information such as the type of account, credit limit granted to his, opening date of the account, the amount of the loan, his payment history and the balance. Moreover, the term of inquiries includes that any consumer gives permission to his lender to ask for a copy of his credit report from a credit reporting agency. The document also contains a list of everyone who has seen his credit report during the last two years. Last of all, a credit reporting agency collects information about bankruptcies, foreclosures from state and country and information on the overdue debts from collection agencies.

➤ What factors influence credit scores?

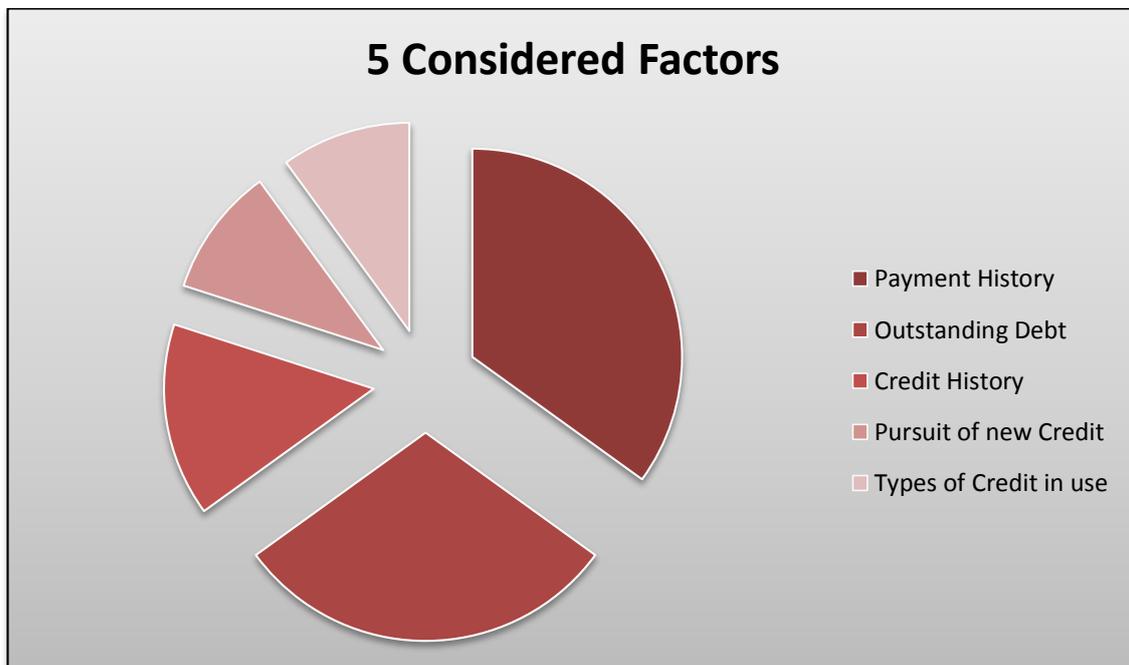
There are a variety of ways that credit scoring companies influence a credit score. Based on the Fair Isaac Corporation credit scoring model, there are five primary areas listed above:

1. Payment history: late payments, accounts referred to collections or bankruptcies will affect negatively the score.
2. Outstanding debt: many scoring models evaluate the amount of debt compared to credit limits. Debt amounts that are close to the credit limit will likely have a negative effect on a score.
3. Credit history: generally, scoring models give more points, when the consumer's credit track record is long enough.
4. Pursuit of new credit: many scoring systems consider whether a consumer has applied for credit recently by looking at inquiries on the credit record. Some of the inquiries can negatively affect a score, some others may be not counted

such as these who are monitoring an account or looking at credit reports. Credit inquiries made by consumers of their own credit records are not included either. Some creditors and credit companies claim that they do not even consider inquiries. Others claim that a lot of inquiries will have only a small impact on credit score.

5. Types of credit in use: although it is generally good to have established credit accounts, too many credit card accounts may have a negative effect on a score. In addition, many models consider the type of credit accounts and give more points to what they consider it is a healthy mix. For example, loans from finance companies may negatively affect a credit score.

Chart 1: The five most considered factors



- What can consumers do to improve credit scores?

Of course, all the consumers would like to know how to improve their credit score in an effort to secure credit at the best possible levels. However, because of the fact that credit scoring utilizes data contained in the credit report, it actually analyzes the credit patterns over an extended period of time. In addition, credit scoring models taking into account, not only the payment history but, also, any older credit related items or occurrences, such as public record items, are also factored into the calculation.

Furthermore, credit scoring models tend to look for a long – term stability. Therefore, radical changes to your credit report may cause a negative impact on your credit score. Each customer must be patient, taking time the improvement. He must expect improvement to take some time because the best approach is to manage his credit responsibility over the long – term and to make sure that the information contained in his credit report is correct.

Briefly, there are some advices for raising your credit score:

1. Pay the bills on time.
2. If any person has missed payments, get current and stay current.
3. Be aware of that paying off a collection account will not remove it from his credit report.
4. If he has troubles about paying the bills, contact with his creditors or meet a legitimate credit counselor.
5. Keep balances low on credit cards and other revolving credit.
6. Do not have too many credit cards, and do not use the maximum credit limit on any of them.
7. Pay off the debt rather than moving it around.
8. Do not close unused credit cards as a short – term strategy to raise the score.
9. Do not open a number of new credit cards that you do not need just to increase your available credit.
10. If consumers have been managing credit for a short time, do not open a lot of new accounts too rapidly.
11. Do rate shopping for a given loan within a focused period of time.
12. Note that it is good to request and check your own credit report.
13. Apply for and open new credit account only as needed.
14. Have credit cards but manage them responsibly.
15. Note that closing an account does not make it disappeared.

➤ What are the benefits of credit score?

There are so many benefits of credit scoring systems. First of all, there is an automation which is faster than ever. Since scores can be availed in minute from any company, the major credit institutions, lenders can process the applications much

faster. For example, nowadays mortgage loans can be processed within an hour instead of a week. In certain, credit score helps in two ways. Firstly a borrower can have the loan immediately and the lender who is granting the loan can check the credibility of the borrower in minutes. Also, credit decisions are fairer. Lenders who are using the credit score can concentrate on the credit risk of the borrower instead of focusing on other factors without meaning like gender, race, religion, nationality and marital status. Credit decisions are taken by the lenders on a free and fair basis. Older credit problems do not count so much. Your past credit problems are not a major problem because credit score always value positive information more than negative information. Any recent good payment options made by applicants which shows that they are doing their best to manage their credit problem regularly, it will have a positive effect on their credit score. Of course, the credit rates can be become lower.

- What happens if a consumer is denied credit or does not get the terms he wants?

If a consumer is denied credit, the creditor must give a notice which notifies the specific reasons that the application was rejected. Indefinite and vague reasons for denial are illegal. Reasons such as: “Your income was low” or “You have not been employed long enough” are acceptable. On the other hand, reasons like: “You did not meet our minimum standards” or “You did not receive enough points on our credit scoring system” are unacceptable.

Sometimes consumers are denied credit because of the information that includes in reports from credit agencies. If so, the creditor must give out the name, address and phone number of that agency that supplied the information. Consumers should contact with the agency to find out what the report said. This information is free if requested within 60 days of the credit denial. The credit reporting agency can inform consumers about their reports, but only the creditor can tell them why applications were denied.

Consumer can ask what characteristics or factors were used in that report, and the best ways to improve the application. If the consumer is offered credit, he has the opportunity to ask whether he got the best rate and terms available and, if not, why. Asking about the best rate is very important. If the consumer is not offered the best

available rate because of inaccuracies in the credit report, it is important to correct the inaccurate information.

➤ Is credit scoring fair?

The financial institutions believe that credit scoring is fair and impartial. It does not use only a specific piece of information as the reason for declining or accepting an application. They test their credit scoring methods regularly to make sure they continue to be fair and unbiased. Responsible lending is essential for the good both of applicants and lenders.

There are two tables with the rankings system of two of the most popular corporations, S&Ps and Moody's.

Table 1: Rankings of S&Ps Corporation.

Rankings	Meanings
AAA	The company is absolutely capable to take care of its liabilities.
AA	The company is capable enough to take care of its liabilities.
A	Despite of the strong feeling, there is a chance of be affected by the economic changes.
BBB	Company has sufficient capacity to meet the obligations.
BB	There is an increased uncertainty because of the economic changes.
B	Economic changes can cause weakness of correspondence.
CCC	The possibility of correspondence is determined by the current business, economic and financial conditions.
CC	The company's ability to cope with is more changeable.
C	The company is bankrupt.
D	There is already defaultness.
+/-	These symbols are used to show the exact class of the company between the rankings AA to CCC.

Table 2: Rankings of Moody's Corporation.

Rankings	Meanings
Aaa	Bonds with excellent characteristics – minimum risk.
Aa	Bonds of high quality. Medium risk in the long term.
A	Bonds with sufficient characteristics and efficient safety margins.
Baa	Bonds with sufficient safety of invested capital.
Ba	Bonds with uncertain prospective and profitable characteristics.
B	Bonds without sufficient investment characteristics and lack of safety.
Caa	Bonds of high risk.
Ca	Bonds with high profitable characteristics which are in a default situation.
C	Very low prospective of satisfaction.
1,2,3	These symbols are used to show the exact class of the company between the rankings Aa to Ca.

3.2 Worldwide Use Credit Scoring Models

Australia

In Australia, credit scoring is widely accepted as the primary method of assessing credit worthiness. Its use is to determine whether credit should be approved to an applicant, or to set of credit limits on credit cards/store cards, in behavioral modeling such as collections scoring, and also in the pre-approval of additional credit to a company's existing client base.

Although logistic or non-linear probability modeling is still the most popular means developing scorecards, various other methods offer extremely powerful alternatives, including Mars, Chaid, Cart, and random forests. The multivariate adaptive regression spines model (MARS) is a form of regression analysis. It is a non-parametric regression technique and can be seen as an extension of linear models that automatically models non - linearities and interactions between variables. The Chaid

model, also, is a type of decision tree technique, based upon adjusted significance testing. It can be used for prediction as well as classification, and for detection of interaction between variables. It stands for CHI-squared Automatic Interaction Detection. In practice, Chaid is often used in the context of direct marketing to select groups of consumers and predict how their responses to some variables affect other variables. Like other decision trees, Chaid's advantages are that its output is highly visual and easy to interpret. Because it uses multiway splits by default, it needs rather large sample sizes to work effectively, than with small sample sizes because the respondent groups can quickly become too small for reliable analysis. Finally, the Classification and regression trees model (CART) is a non-parametric decision tree learning technique that produces either classification or regression trees, depending on whether the dependent variable is categorical or numeric, respectively.

At present Veda Advantage, the main provider of credit file data, only provides a negative credit reporting system which contains information on applications for credit and adverse listings indicating a default under a credit contract. This makes accurate credit scoring difficult for financial institutions if they have no existing relationship with a prospective borrower.

Austria

In Austria, credit scoring system is like a blacklist. Consumers which did not pay bills end up on the blacklists that are held by different credit companies. If there is a black list in the name of an applicant, may result in the denial of contracts. Just specific branches like telecom carriers use the list on a regular basis. Financial institutions do not use these lists, but rather inquire about securities and income of the consumer.

According to the Austrian Data Protection Act, which is a European Union directive and regulates the processing of personal data within the European Union, so it is an important component of EU privacy and human rights law, consumers must opt-in for the use of their private data for any purpose. Consumers can also retrieve the permission to use the data later, which makes any further distribution or use of the collected data illegal. They also have the right to get a free copy of all data held by the credit companies once a year. Wrong or unlawfully collected data must be deleted or corrected.

Canada

In Canada, the system of credit reports and scores is very similar to that in the United States, with two of the same reporting agencies active in the country: Equifax and Trans Union. There are, however, some key differences. The most important difference is that, unlike the United States, where a consumer is allowed only one free copy of their credit report a year, in Canada, the consumer may order a free copy of their credit report any number of times in a year, as long as the request is made in writing, and as long as the consumer asks for a printed copy to be delivered by mail. This request by the consumer is noted in the credit report, but it has no effect on their credit score.

According to Equifax's Score Power Report, FICO scores range between 300 and 900. The Government of Canada offers a free information called Understanding Your Credit Report and Credit Score. This provides sample credit report and credit score documents, with explanations of the notations and codes that are used. It also contains general information on how to build or improve credit history, and how to check for signs that identity theft has occurred. The publication is available online at the Financial Consumer Agency of Canada. Paper copies can also be ordered at no charge for residents of Canada.

India

In India, there are four credit information companies licensed by Reserve Bank of India. The Credit Information Bureau Limited (CIBIL) has been functioning as a Credit Information Company from January 2001. Subsequently in 2010, Reserve Bank of India gives licenses to Experian, Equifax and Highmark to operate as Credit Information Companies in India.

Although all the four credit information companies have developed their individual credit scoring systems, the most popular is CIBIL. The CIBIL credit score is a three-digit number that acts like a summary of individual's credit history and credit rating. This score ranges from 300 to 900 with 900 being the best score. Individuals with no credit history will have a score of -1. If the credit history is less than six months then score will be 0. CIBIL credit score takes time to build up and usually it takes between 18 and 36 months of credit usage before a decent credit score.

Norway

In Norway, credit scoring systems are provided by three credit scoring agencies: Dun & Bradstreet, Experian and Lindorff Decision. Credit scoring is based on publicly available information such as tax returns, demographic data, taxable income and any non-payment records that might be registered on the credit scored individual. Upon being scored, an individual will get a notice (which will be written or in the form of an e-mail) from the scoring agency stating who performed the credit score as well as any information provided in the score. Another method is that, many credit institutions use custom made scorecards based on any number of parameters. Credit scores range between 300 and 900.

South Africa

In South Africa, credit scoring is used throughout the credit industry. Currently all four retail credit companies offer credit scores. The data stored by them include both positive and negative data, increasing the predictive power of the individual scores. Trans Union (formerly ITC) offers the Empirical Score which is, in its 4th generation. The Empirical score is segmented into two suites: the account origination (AO) and account management (AM). Experian South Africa likewise has a Delphi credit score with their fourth generation about to be released (late 2010). Compuscan released CompuScore ABC in 2011. This scoring suite predicts the probability of customer default throughout the credit life - cycle.

Sweden

In Sweden, there is, also, a system for credit scoring that aims to find people with bad payment attitudes. It has only two levels, good and bad. Anyone who does not make debt payments on time, and continues not to make payments after they are reminded, will have their case forwarded to the Swedish Enforcement Administration which is a national authority which collects debts. The very appearance of a company as a debtor in this authority will render a mark among private credit bureaus, however, this does not apply to a private person. This mark is called non-payment record and can according to the law be stored for three years for a private person and five years for a company. This kind of non-payment record will make it very difficult to get a loan, a rental apartment, a telephone subscription or a job with cash handling. The financial

institutions of course use income and asset figures in connection with loan assessments.

If one gets an injunction to pay by the Enforcement Administration, it is possible to object to it. Then the one requesting the payment must show the correctness in district court. Failure to object is seen as admitting the debt. If the debtor loses the court trial, costs for the trial are added to the debt. Taxes and authority fees must always be paid on request unless payment has already been made.

United Kingdom

In United Kingdom, the most popular statistical technique used is logistic regression to predict a binary outcome, such as bad debt or no bad debt. Some companies also build regression models that predict the amount of bad debt a customer may have. Typically, this is much harder to predict, and most of them focus only on the binary outcome.

Credit scoring is only closely regulated by the Financial Services Authority when used for the purposes of the Advanced approach to Capital Adequacy under Basel II regulations.

It is very difficult for a consumer to know in advance whether they have a high enough credit score to be accepted for credit with a particular lender. This is due to the complexity and structure of credit scoring, which differs from one lender to another. Also, lenders do not have to reveal their credit score head, nor do they have to reveal the minimum credit score required for the applicant to be accepted. Simply due to this lack of information to the consumer, it is impossible for him or her to know in advance if they will pass a lender's credit scoring requirements.

If the applicant is declined for credit, the lender company is also not obliged to reveal the exact reason why. However Industry Associations, such as the Finance and Leasing Association, oblige their members to provide a high level reason. Credit company data sharing agreements also require that an applicant declined due to data is told that this is the reason and the address of the credit company be provided.

United States

In the United States, a credit score is a number based on a statistical analysis of a person's credit files. A credit score is primarily based on credit report information, typically from one of the three major credit companies: Experian, Trans Union, and Equifax. Income is not considered by them when calculating a credit score.

There are different methods of calculating credit scores. FICO score from Equifax, the most widely known type of credit score, is a credit score developed by FICO, previously known as Fair Isaac Corporation. It is used by many mortgage lenders that use a risk-based system to determine the possibility that the borrower may default on financial obligations to the mortgage lender. All credit scores have to be subject to availability. It is widely recognized that FICO is measure of past ability to pay. FICO produces scoring models that are most commonly used, and which are installed at and distributed by the three largest national credit repositories in the U.S (Trans Union, Equifax and Experian) and the two national credit repositories in Canada (Trans Union Canada and Equifax Canada).

New credit scores have been developed in the last decade by companies such as Scorelogix, PRBC, L2C, Innovis etc. which do not use data to predict creditworthiness. Scorelogix's JSS Credit Score uses a different set of risk factors, such as the borrower's job stability, income, income sufficiency, and impact of economy, in predicting credit risk. Most lenders today use some combination of company's scores (FICO) and alternative credit scores to develop a better insight into their borrower's ability to pay.

L2C offers an alternative credit score that utilizes payment histories to determine creditworthiness and many lenders use this score to make lending decisions. Many lenders use Scorelogix's JSS score since this scores factors job and income stability to determine if the borrower will have the ability to repay debt in the future. It is estimated that FICO score will remain the dominant score but in all likelihood it will always be used in conjunction with other alternative credit scores which offer new layers of risk insights.

Consumers wishing to obtain their credit scores can in some cases purchase them separately from the credit companies or can purchase their FICO score directly from FICO. Credit scores are also made available for "free" through subscription to one of the many credit report monitoring services available from the credit companies or other third parties.

Under the Fair Credit Reporting Act, a consumer is entitled to a free credit report within 60 days of any adverse action (e.g. being denied credit, or receiving substandard credit terms from a lender) taken as a result of their credit score. Under the Wall Street reform bill, a consumer is entitled to receive a free credit score if they are denied a loan or insurance due to their credit score.

In the United States, generic FICO scores range from 300-850. The performance definition of the FICO risk score is to predict the likelihood that a consumer will go 90 days past due or worse in the subsequent 24 months after the score has been calculated. The higher the consumer's score, the less likely he will go 90 days past due in the subsequent 24 months after the score has been calculated. Because different lending uses (mortgage, automobile, credit card) have different parameters, FICO algorithms are adjusted according to the predictability of that use. For this reason, a person might have a higher credit score for a revolving credit card debt when compared to a mortgage credit score taken at the same point in time. As an individual borrows more money, its credit score decreases.

CHAPTER 3

Literature Review

1. Introduction

Credit risk measurement has evolved dramatically cause of many economic problems. Among these problems have been a worldwide structural increase in the amount of bankruptcies and a trend towards disintermediation by the highest quality and largest borrowers. There is, also, a declining value of real assets in many markets, more competitive margins on loans and dramatic growth of off – balance sheet instruments with inherent default risk exposure including credit risk derivatives. All these have made development of credit risk more important than ever before. There are many changes in it over the last 20 years.

For managing credit risk, financial institutions developed various models to evaluate the financial performance of consumers. They made new and more sophisticated credit scoring systems, as well as, measures of credit concentration risk such as a whole portfolio risk. They, also, developed new models to price it like RAROC and models to measure better the credit risk of off - balance sheet instruments. Results were validated by various supporting (regression, discriminant, etc.) analyses and by expert judgments based on data.

2. Scorecards

A complete risk management system must include many different types of scorecards. These are mathematical models, which attempt to estimate the probability that a customer will expose a specific behavior such as loan default or bankruptcy. Some types of them are the application scorecard, the behavioral scorecard, the collection scorecard and the fraud scorecard.

2.1 Application Scorecards

Application scorecards connect the characteristics on the application and the creditworthiness of a customer, using only the application and the credit office data.

All the payments could be identified statistically after a 6 month period. Three to six months are needed to be the testing period and have the first results and defaulters. Thomas et al [2002] advised that such competitions should be continued at least for twelve months more. In other words, these quantifies the risks, by evaluating the social, demographic, financial and other data collected at the time of application. This kind of scorecards includes the most important variables and characteristics.

In a chance that financial institutions want to change their policy, according to Hopper and Lewis [1992], they should make some tests. Instead of replacing the old scorecard model by the new one, the new model should be tested on a sample of customers and compared with the results of the initial group where the old one is still in place. So, all the changes will depend on the results of this test. The only issue of such an approach is that the effects of a scorecard on the default rate of a portfolio are long term effects. Thus, this process can be productive and conclusive to a credit policy, after a long time.

2.2 Behavioral Scorecards

Behavioral scorecards use characteristics of customers' recent behavior to predict their potential risk of being defaulters. These models helps the institutions to understand the customers and respond to their individual needs. The variables are related to the history of the customer, as the results of the repayment and the usage behavior of the customer. It is recommended about twelve to twenty months of observation to conclude a score. There will be the definition of 'bad' and 'good' customers. 'Bad' customers for those who make a default and, also those who present some characteristics about potential defaulters. In contrary, 'good' customers for those that there is no any evidence of defaultness.

According to the literature, typical variables could be average, minimum and maximum levels of balance, debit and credit turnover. Additional information could, also, be the status of the account, such as the number of times that customer outrun its limits, how many warning letters had been sent and how long since any repayment had been made. In order to estimate the payments, those variables could be combined into weighted averages or ratios of performances at the start date with those at the end date of observation.

Lim & Sohn [2007] tried to make an innovative behavioral scoring model. This model takes into consideration the time that someone's payment behavior could be affected, which means that characteristics incorporated in the model will vary upon time. The model is based on a k - means algorithm that allows to gather similar data, trying to be more accurate. The observation period is not something defined. Basically, their model takes into account the time factor and it predicts a certain type of borrower at a desired point of time. It, also, put together all the customers based on their behavior. They concluded that this model was improving the performance of the currently static model in predicting bad losses. The main advantage of their model is that creditors will be more accurate for predicting customers with a high probability of default over time.

2.3 Collection Scorecards

Collection scorecards quantifies the probability of recovery of the outstanding balance for those accounts in collections. Debtor's willingness and ability to pay, helps to define what actions should be done to increase collections. The data were similar with these at the behavioral scorecards.

Thomas et al insisted on doing tests and adopting different possible strategies in order to find the most effective and efficient model.

2.4 Fraud Scorecards

Fraud scorecards are used to detect customers who are likely to default, and the reason for this may include fraud, according to Bolton and Hand [2002]. These score applicants based on the probability that an application may be fraudulent. Thus, financial institutions could have the possibility to be notified of the potentially fraudulent applications' before booking an account.

This kind of scorecards is a model built on experience of past cases based on the hypothesis that it will follow the same way this year. It facilitates fraud detection and prevention helping instantly decide which of the applications should be rejected or set aside for more in depth evaluation due to high fraud probability. The result is simple, either a genuine customer or a fraudster. Fraud scoring helps lenders to increase their profits and enhance their customer service, by identifying potential fraud.

2.5 Profit Scorecards

Generally, there are two types of accounts. Those that bring profit to the institution and those that generate net losses. The major issue is to assign them a higher limit by detecting. There are several parameters that financial institutions have to take into consideration. According to Thomas et al, some of them are the funding costs, the acquisition costs, the timing of early payment, the cross – selling opportunities and the net present value calculation.

When the process is finalized, the lender will have to decide how to use the score. Similar to behavioral scorecards, there is the definition of ‘bad’ and ‘good’ customers. But there is a possibility of mistake and a ‘bad’ customer to be classified as a ‘good’ one. To prevent this kind of errors, the lender can have three options. First of all, the most simply way is to reject those customers from the first time. Despite the fact that they are always paying on time, they do not represent a high portion of the total profit of the bank. Another way is to propose to those customers products or services that could satisfy them at this time and bring some profit. Finally, the lenders could accept them knowing that they are not profitable. There is the possibility, some of them to turn into profitable ones while the rest will possibly stop their contract. Many times, companies can use a combination of the second and the third options.

3. Review of Credit Score Techniques

According to Lai et al. [2006], there are many statistical techniques that can be used to build and examine credit scoring models and different scorecards that will be integrated in the credit scoring solution.

3.1 Discriminant Analysis

Discriminant analysis creates an equation which tries to minimize the possibility of misclassifying cases into their respective groups or categories. The goal of this statistical analysis is to combine the variable scores in a such way so that a new composite variable, known as the discriminant score, is produced. In other words, the discriminant score is a weighted linear combination of the discriminating variables.

This analysis involves the creation of a linear equation like regression that will predict in which group the case belongs to. The form of the equation or function is:

$$D = v_1X_1 + v_2X_2 + \dots + v_iX_i + a$$

Where: D = discriminate function

v = the discriminant coefficient or weight for that variable

X = respondent's score for that variable

a = a constant

i = the number of predictor variables

More analytically, the v's are unstandardized discriminant coefficients. These maximize the distance between the means of the dependent – criterion variable. On the contrary, standardized discriminant coefficients can be used like beta weight in regression. Good predictors tend to have large weights.

However, there are some assumptions of this type of statistical analysis. First of all, the observations must be part from a random sample and each predictor variable follow the normal distribution. There must be at least two groups or categories with each case belonging to only one group so that the groups are exclusive. In that way, the groups must be well defined and clearly differentiated from any other group. Putting a median split on an attitude scale is not a natural way to form groups. Finally, groups sizes of the dependent variables should not be big and should be at least five times the number of independent variables.

According to literature review, Durant [1941] was the first analyst who introduced discriminant analysis for categorizing financial data. Beaver [1966] tried to apply the univariate discriminant analysis on financial ratios and he found out that the cash flows to debt ratios were the best predictors for forecasting firms' distress. Boggess [1967] believed that this particular method was the most efficient in order to determine all the weights and scores for the different characteristics.

On Altman's study [1968], which was based on a sample including 134 firms, used a multiple discriminant analysis model known as Z – score model to predict the

repayment ability of his firms. Altman, also, used this analysis as a classification tool in other papers (Altman [1993] and Altman et al. [2007]). Bates discussed and decided to estimate a discriminant function based on multiple discriminant analysis. In that way, he could identify the successful loan applications from the frauds. On Apilado's study [1974], there is a comparison between the use of multivariate discriminant analysis with the univariate discriminant analysis. He concluded that the first one analysis had greater predictive powers than those constructed by the univariate model.

Eissenbeis [1977] had discussed a number of statistical problems while applying this technique. Some of them were the group dispersions, the distribution of the variables, the reduction of dimensionality, the meaning of the significance of individual variables, the definition of the groups and the choice of the appropriate probabilities and costs of misclassification. On Reichert's et al. study [1983], the main topic was the application of the multiple discriminant analysis. They tried to set the requirements to implement such techniques properly and to evaluate the consequences of the case of not fulfilling those. They, finally, concluded that it was possible to develop a model which could fulfill most of the assumptions behind multiple discriminant analysis.

According to Romer et al. [1990], there were, also, many problems applying the discriminant analysis. So, Crook et al. [1992] tried to investigate how this analysis could be used for credit card companies. On the other hand, Lee et al. [1999] adopted this method to conduct bankruptcy predictions and the result was that it was the most commonly used technique applied for that situation. Kim, Ye & Lee [2000] tried to find a classification analysis on the real estate markets in Korea and to predict the consumer behaviors using discriminant analysis.

There were many arguments about the issue of discriminant analysis such as the efficiency, the implementation and the interpretation when apply to large sample, the need for statistical assumptions, the need for ordered categorical variables and outliers of sensitivity. The most recently work has been done by Mileris [2010], which had shown that banks are capable to measure the default probability of their clients by using discriminant analysis and simple Bayesian classifier. Mileris listed two

advantages of the analysis which were the easiness to implement and to interpret. Moreover, Altman et al. [1994] and Yobas et al. [2000] examined the discriminant analysis and they came to the same conclusion, which was that this method was outperforming neural networks.

3.2 Logistic Regression

Logistic regression is more commonly used when there are only two categories of the dependent variable than discriminant analysis. It determines the impact of multiple independent variables and at the same time predicts the membership of one or other of the two dependent variable categories. It is based on the concept that each single attribute should be tested before taking into account in the model. Logistic regression uses the binomial probability theory in which there are only two values to predict: either the probability is 1 or 0. It forms a best fitting equation or function using the maximum likelihood method, which maximizes the probability of classifying the observed data into the appropriate category given the regression coefficients.

Like any ordinary regression, logistic regression provides a coefficient 'b', which measures the contribution of each independent variable to variations of the dependent variable. The aim is to predict correctly the category of outcome for individual cases using the most simple model.

The form of the equation or function is:

$$\text{logit}[p(x)] = \log \left[\frac{p(x)}{1 - p(x)} \right] = a + b_1x_1 + b_2x_2 + b_3x_3 \dots$$

Instead of using a least – squared deviations criterion for the best fit, it uses a maximum likelihood method, which maximizes the probability of getting the observed results given the fitted regression coefficients. The only problem is that the goodness of fit and overall significance statistics used in logistic regression are different from those used in linear regression.

So p must be calculated from the following formula:

$$p = \frac{\exp(a+b^1x^1+b^2x^2+b^3x^3 \dots)}{1 + \exp(a+b^1x^1+b^2x^2+b^3x^3 \dots)}$$

Where: p = the probability that a case is in a particular category

\exp = the base of natural logarithms

a = a constant

b = the coefficient of the predictor variables

There are some assumptions, as well, of this kind of regression that they have to be taken into consideration. First of all, regression does not assume a linear relationship between the dependent and independent variables. The first kind of variables must be a dichotomy, into two categories. On contrary, the independent variable does not need to be interval, nor normally distributed, nor linearly related, nor of equal variance within each group. Also, the categories must be exclusive like at the discriminant analysis, so any case can be set only in one group and every case must be a member of one of the groups. Finally, larger samples use logistic regression because maximum likelihood coefficients are large sample estimations. A number of 50 cases per predictor is recommended, at minimum.

According to Orgler [1970] who was the first analyst that used the multivariate regression analysis, tried to predict whether a customer will default or not. He took into consideration a specific assumption that if the observations for fitting a logistic regression model satisfy certain normality assumptions, the maximum likelihood estimation of the regression coefficients are the discriminant function estimation. Haggstrom's [1983] work showed that these estimations and the associated test statistics for variables' selection can be calculated by using the least squares regression techniques. In addition, Steenackers & Goovaerts [1989] tried to make a model based on a stepwise logistic method. Another approach was this by Banasik [1996] who tried to compare a scorecard built on the full population with a scorecard built on subpopulation. He reached to result that the second one scorecard tend to reject fewer applicants than the first option. A such splitting on subpopulations is not a worthwhile mean for all the variables' splits.

According to Berkowitz & Hynes [1999], they used logit regression in order to estimate personal bankruptcy on mortgages. On West's approach [2000], the logistic regression was a good alternative to the neural models for building a scorecard. Moreover, in Cramer's paper [2004], a bank applied this method with state dependent sample selection to predict loans that may default. He concluded that the state dependent technique did not succeed to work because all data did not satisfy the standard logit model. Finally, Cramer made several changes on this model and he found out that a bounded logit with a ceiling of less than 1 fit the data better.

3.3 Probit regression

Probit regression is a technique which is used when the dependent variable is dichotomous (1 or 0). This is based on the cumulative normal distribution. It assumes that a theoretical index $z(i)$ is existed which is not observed or measured, but it is linked to an explanatory variable $x(i)$ whose data has been collected on. The problem was how to obtain estimation for the explanatory variable while at the same time obtain information about the underlying unmeasured scale of index $x(i)$. This was something that has been solved. The most important aspect is that it outputs the probability of the event which will fall between 1 and 0.

The form of the equation or function is:

$$Prob(y = 1) = \Phi(a + b_1x_1 + \dots + b_nx_n)$$

Where: y = dichotomous

$\Phi(x_1, \dots, x_n)$ = independent variable

α = a constant

b = coefficients

First, Badu & Daniels [1997] examined the relative internal factors which used in grading municipal general obligation bond ratings. In another paper of them [2002] tried to examine the probability of default, the credit risk premium and their impact on net interest cost using data since 1995. They concluded that the probability of default measured by probit regression is determined by population size and change, ratio of

long term debt to total debt, per capital income, real estate taxes and the organization form of government.

In Boyes et al. [1989] approach, it is presented a model for the credit estimation focusing on expected earnings. They examined the way that maximum likelihood estimation of probability of default could be come by a bivariate censored probit frame and a choice – based sample originally intended for discriminant analysis could be used. Crook [2001] set an important question: what factors determine whether a credit applicant is likely to be rejected and discouraged from further applications? He chose to use an univariate probit model with standard errors to answer it.

Moreover, Tsaih et al. [2004] used the probit regression analysis to develop a sufficient credit scoring model based on a N – tier architecture integrated with the idea of Model View Controller. This would allow the scoring model to be easily altered accordance the change or business environment by the model managers. There was an advantage of that specific design which was the reduction of the consuming time for the system engineers as the effort and the time in communicating with model managers would be reduced.

Another application of probit regression analysis was from Wallace [1978, 1981] who used regression and multivariate probit models to estimate bond ratings and revenue bond issues from a sample of 106 new general obligation in the state of Florida.

3.4 Neural Networks

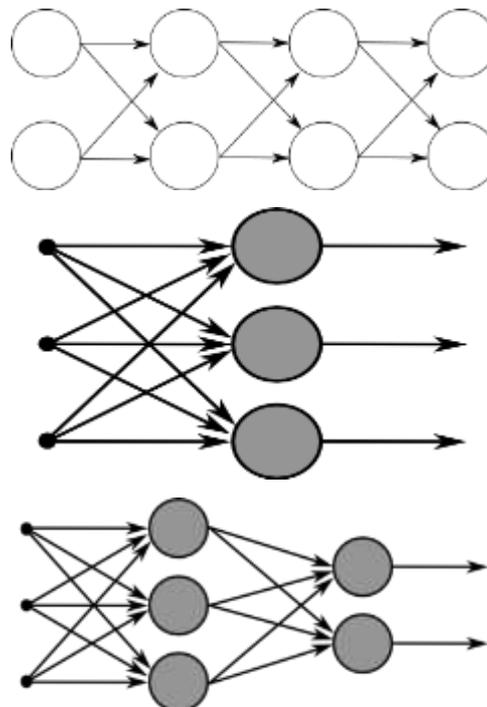
Neural networks provide a new alternative to classical statistical techniques. They are extremely flexible models that combine characteristics in a variety of ways using many kinds of algorithms. Their predictive accuracy can be far superior to scorecards. They are used particularly in situations where the dependent and independent variables exhibit complex of a non – linear relationships and the systems, which are created, are not easily modeled with a closed – form equation. Therefore, there are many types of neural networks and they are divided into two different categories. These categories are based on the elements which can either be connected to each other, enabling the influence between other elements or take inputs only from the previous layer and send outputs to the next layer. The functional approximation which

can be computed with neural networks is to estimate the prediction of errors when new values are presented to the specific network.

However, it is practically impossible to explain or understand the score that is produced for a particular application in any simple way. A neural network of superior predictive power is therefore best suited for certain behavioral or collection scoring purposes. At these, the average accuracy of the prediction is more important than the insight into the score for each particular case. Neural network models cannot be applied manually like scorecards, but require software to score the application, although, their use is just as simple as the other model types.

For example, the most commonly known neural network is the feed forward systems. They are the simplest form of neural networks. These models contain only forward paths like the following layout.

Chart 2: Neural networks examples.



In a feed forward system, there are distinctive layers, with each layer receiving inputs from the previous one and outputting to the next layer. There is no feedback, so the signals from one layer are not transmitted to a previous layer. The weights from each

row in layer $i-1$ to the row in layer i are defined into a matrix w_i . Each row corresponds to an element in $i-1$ and each column corresponds to an element in i .

Abdou et al. [2008] used neural networks with successful applications in many financial institutions and banks. Researches by Lee & Chen [2005], Lee et al. [2002], Zekic - Suzac et al. [2004], Malhotra [2003] and Ong. Huang & Tzeng [2005] had compared traditional and advanced statistical techniques and they tried to include feed forward nets and back propagation nets.

Masters [1995], Sarlija & bensisic [2004], and Ganchev et al. [2007] focused on the one of the two most known neural networks, the probabilistic network. This was used to estimate binary outcomes. On the other hand, Bishop [1995], Desai et al. [1996], Dimla & Lister [2000], Reed & Marks [1999], Trippi & Turban [1993]. West [2000] and Erbas & Stefanou [2008] used the second version of neural networks, known as multilayer perceptron or feed - forward networks.

Some of the first papers dealing with neural networks were by Dutta & Shekhar [1988] and Surkan & Singleton [1991]. They applied this method to improve risk ratings of bonds. Based on that, Hutchinson et al. [1994] figured out that in many cases the network pricing model outperforms the Black – Scholes model. Franses & Van [1998] examined if the artificial neural network should be used in forecasting the daily exchange rate return. He concluded that something like that must not be used. Moreover, Plasman et al. [1998] applied the feed – forward network to examine the estimation of performance of structural and random walk exchange rate models. They found out that there was not any non – linearity in the monthly data, especially in a sample of US dollar rates in Deutsche marks, British pounds and Japanese yen.

Another prospective was established by Anders et al. [1998] based on his effort to explain the prices of call options on the German stock index DAX. They insisted on that neural networks performed better than the Black – Scholes model. Stern [1996] was the first analyst and after him, Erbas & Stefanou that mentioned specific characteristics such as memory, robustness, ability to handle large amount of data, ability to generalize, absence of any explicit problem description, need for less statistical assumptions according to Santin et al. [2004], non parametric and non linear

method based on research of Santin et al. and Hill et al. [1994], which caused many arguments. In Dimla & Lister [2000] paper, neural model based on modular tool condition monitoring system was presented for cutting tool – state classification. They characterized neural network as a robust mathematical processing device capable of non linear modelling and function approximation because of the absence of clear problem description and the capability of handling large amounts of data.

However, there were some disadvantages about neural networks. In Castillo, Marshall, Green & Kordon [2003], Feraud & Cleror [2002] and Nath, Rajagopalan & Ryker [1997] studies, the performance of these networks when have to be applied to small samples had been clearly pointed out. Chung & Gray [1999] and Graven & Shavlik [1997] had, also, examined and criticized for the long training time of networks and, therefore, for its applicability to credit scoring problems. Indeed, Yim & Mitchell [2005] made ascertain that the issues about selection time and overfitting when dealing with large datasets, were very important. Finally, Hills et al. [1994] mentioned that neural networks were hard to interpret, as Santin et al. [2004] raised the issue of trials and error processes.

Although, according to studies of Weigend & Neueier [1995] and Han et al. [1996], there were to ways to improve the networks: the pruning and the hybrids. Pruning aimed at decreasing the size of these holding their generalization ability. This included some methods such as simple weight elimination by Weigend et al. [1991], Bebis et al. [1997] and Cunha [2000] and generic algorithms by Miller et al. [1989], Bebis et al. [1997] and Yao [1997]. Yim & Mitchell [2005] pointed out that the pruning methods had been applied especially to predict firm bankruptcy. On the other hand, Altman et al. [1994], Markham & Ragsdale [1995] and Han et al. [1996] were the first authors that suggested to combine the neural networks, so the new model / hybrid could be benefited from the other techniques. By using these, the risk of overfitting would be less and the neural networks would be able to use the outcome of another model as the amount of data were reduced. The result was that hybrid neural network models presented a highly level of accuracy for bankruptcy prediction.

Moreover, Lee et al. [1996] tested the performance of a two stage hybrid modelling procedure with artificial and multivariate adaptive regression splines (M. A. R. S.) in

predicting loans failure. Lee & Chen [2005] concluded that this model used traditional techniques like discriminant analysis and logistic regression and it was an efficient alternative to forecast if a loan would default or not. Another trial was made by Chen & Huang [2003], who combined both neural networks and generic algorithms. Neural networks were used to classify the applications either accepted either rejected to minimize the borrowers' risk. Additionally, the generic algorithms were used to reassign rejected applications to the preferable accepted class which could balance the adjustment cost and customer preference. They came to the conclusion that there were many attractive features for aid of the computer credit analysis system.

There were, finally, many hybrids which appeared like this one by Hsieh [2005] and Yim & Mitchell [2005]. Hsieh made an hybrid system by combining clustering and neural network techniques and Yim & Mitchell tested a relatively technique to predict the corporate distress in Brazil. They concluded that hybrid networks outperformed all other models while predicting one year prior to the event.

3.5 Time Varying Model

Time varying models are based on time series. These series are chronological sequence of observations for a specific predictor variable. The main goal is to predict the future probable value of any outcome. The data which are concluded from the observations can be selected and collected on regular intervals like years, months, quarters and days. This means that there is no need the sample selection to be regular.

The form of the equation is:

$$y_t = f(y_{t-1}, y_{t-2}, \dots, y_{t-k}) + e_t$$

Where: y = the outcome

$f(y_{t-1}, y_{t-2}, \dots, y_{t-k})$ = the values of at time $t-1, t-2, \dots, t-k$

e_t = the errors

Anderson & Goodman [1957] examined the Markov chain and he realized that it was a suitable probability model for certain time series in which the observation time was

the category that an individual could default. Cyert, Davidson & Thompson [1962] studied the long – term, expected uncollectible amount in each age category by using techniques of Markov chains. The same authors, in a later study [1968], tried to develop another Markov chain model as long as they wanted to estimate the behavior of charge accounts especially in retail establishments.

Dirickx & Wakeman [1976] referred that the first model of credit granting process was that by Bierman & Hausman [1970]. They specialized at the multi – period analysis (Dynamic Programming) combined with the Bayesian analysis allowing information to update. Moreover, Seow & Thomas [2006] made up a model to subscribe lenders decision problem in the credit granting process. The main goal of that study was to develop a model of adaptive dynamic programming in which Bayesian techniques were useful to predict better a take – up probability distribution. The most important clue about these techniques were that they allowed previous responses to affect the decision process. This type of modelling techniques were usually used for making behavioral scorecards.

3.6 k – Nearest Neighbors’ Algorithm

The k – nearest neighbors’ algorithm is a non – parametric method which is used for classification and regression. It is one of the most easiest machine learning algorithms. In both cases, the input consists of the k – closest training examples in the feature space. On the contrary, the outputs are depending on whether the algorithm is used for classification or regression. For the first situation, an object is classified by a majority vote of its neighbors. The k number must be positive and small. If $k = 1$, the object is allocated to the class of that single nearest neighbor. On the other hand, the output is the property value for the object and this is the average of the values of its k – nearest neighbors. However, both for classification and regression, it can be useful to weight the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones.

The form of the equation is:

$$w_i = \frac{i}{\sum_{i=1}^k i}$$

Where: $w_k \geq w_{k-1} \geq \dots \geq w_1 > 0$

i = the most distant neighbors

k = the closest neighbors

Choosing the best k, data must be considered and examined very carefully. Generally, larger values of k reduce the effect of errors on the classification. It is helpful to choose k to be an odd number as this avoids tied votes. The only disadvantage of this algorithm is that it is sensitive to the local structure of the data.

Fix & Hodges [1952] and Cover & Hart [1967] were the first analysts who originally introduced the idea of k – NN algorithm. Hills [1966] presented a method called ‘closest neighbor’ rules in which the observations could be classified on a category of population based on the similarity they presented, after discounting the losses for a possible misclassification. Another approach was that by Henley & Hand [1996], who applied this particular method as a standard non – parametric technique used for probability density function estimation and classification.

3.7 Risk - Adjusted Return on Capital (RAROC)

At 1970s, Banker Trust presented the idea of RAROC model. Because of the continuous growth of financial institutions, the creation of banking corporations, the need of maximizing the worth of their stocks and their involvement in many different financial ways, decision makers had the need to compare the returns on several different projects with varying risk levels. Today, most of the financial institutions use this method instead of estimating the creditworthiness.

RAROC is a risk – based profitability measurement structure for analyzing risk – adjusted financial performance and providing a consistent view of profitability across the business. However, more and more return on risk adjusted capital is used as a

measure which is based on the capital adequacy guidelines as notified by the Basel Committee.

RAROC is defined as the ratio of the risk adjusted return to the economic capital. The last one is the amount of money which is needed to secure the survival in a worst – case scenario and it should cover all relevant risks, credit risk in this specific case. Economic capital is often calculated by Value – at – Risk (VaR). According to Jorion [2001], VaR is a measure of the total risk in a portfolio, as mentioned before. RAROC systems allocate capital for two main reasons, risk management and performance evaluation. For risk management purposes, the main goal of allocating capital to individual business units is to determine the bank's optimal capital structure - that is economic capital allocation is closely correlated with individual business risk. As a performance evaluation tool, it allows banks to assign capital to business units based on the economic value added of each unit.

The form of the equation is:

$$\begin{aligned} RAROC &= \frac{\textit{Adjusted income}}{\textit{Economic capital}} \\ &= \frac{\textit{Revenue} - \textit{Expenses} - \textit{Expected Loss} + \textit{Income from capital}}{\textit{Capital}} \end{aligned}$$

In financial analysis, riskier projects and investments must be evaluated differently from their riskless counterparts. By discounting risky cash flows against less risky cash flows, RAROC accounts for changes in the profile of the investment. In general, the higher the risk, the higher the return. Thus, when companies need to compare and contrast two different projects or investments, it is important to take into account these possibilities.

For example, suppose there are two investment opportunities, A and B. RAROC can show which of the two investments is the better one, but it does not notify if it is a good idea to make the specific investment.

If the primary goal for a company is to add economic value, and if A has a higher RAROC than B, then the decision rule must be:

$$\text{RAROC (A)} > \mu \longrightarrow \text{Invest in A}$$

Where: μ = hurdle rate

Hurdle rate is the minimum rate of return on an investment that a financial institution is willing to accept, given its risk and the opportunity cost of forgoing other investments. At the most times, the hurdle rate should be equal to the cost of equity capital.

3.8 Altman Z – Score

Altman [1968] was the first who used the linear multivariate model, known as Z – score to estimate the probability of default. Meyer & Pifer [1970], Altman [1981], [1983], [1984] were some other approaches by this specific method. The output of a credit-strength test that calculates a publicly traded manufacturing company's likelihood of bankruptcy. The Altman Z - score is based on five financial ratios that can be calculated from data found on a company's annual report.

The form of the equation is:

$$Z = k_1X_1 + k_2X_2 + \dots + k_nX_n$$

Where: Z = cut – off score between bankrupt and not companies

k = coefficients of variation

X_1, X_2, \dots, X_n = independent variables / financial ratios of business

The Z - score model, as it is a compound ratio of weakness, is based on logistic financial ratios. The general idea is affected by liquidity ratios, profitability ratios, cash flows ratios and leverage ratios. More analytical:

$X_1 = \text{Working capital} / \text{Total assets}$

This ratio shows that, in general lines, a company which has repeated losses, it shows reduces of working capital compared to its total assets.

$X_2 = \text{Retained earnings} / \text{Total assets}$

This ratio shows the possibility that an institution can reinvest the earnings by itself.

$X_3 = \text{Earnings before taxes and interest} / \text{Total assets}$

This ratio adjusts the profits of a company for different income tax rates and it makes some changes to the leverage which are caused by the lending. These changes make more sufficient calculation of the total assets.

$X_4 = \text{Market value of equity} / \text{Total liabilities}$

This index gives an indication of how the total assets of a company may lose value prior debts outweigh its assets.

$X_5 = \text{Net sales} / \text{Total assets}$

This index calculates the ability of a company to make profits.

The Z – score model is differentiated between a public and a private company.

For a public institution, the score is calculated by the specific equation:

$$Z = 1,2X_1 + 1,4X_2 + 3,3X_3 + 0,6X_4 + 1,0X_5$$

For a healthy public enterprise, the score must be in a safe zone $Z > 2,99$. A middle situation, known as the grey zone, is $1,81 < Z < 2,99$ and finally, the distress zone is $Z < 1,81$.

On the other hand, for a private company, the score is:

$$Z = 6,56X_1 + 3,26X_2 + 6,72X_3 + 1,05X_4$$

For a healthy private enterprise, the score must be in a safe zone $Z > 2,60$. A middle situation, known as the grey zone, is $1,1 < Z < 2,59$ and finally, the distress zone is $Z < 1,1$.

The application of this model presupposes that the independent variables follow the normal distribution, with the same variance and different mean.

Altman [1977] decided to cooperate with R. G. Haldeman and P. Narayan to improve the previous model so it can take into consideration new data from the market. The advanced model is known as ZETA – score and it is analyze deeper and more efficient the changes of the market. The equation is exactly the same with the previous one. Although, new ratios have been selected and these are:

X_1 = Return of assets = Earnings before taxes and interest / Total assets

X_2 = Stability of earnings

X_3 = Debt service = Earnings before taxes and interest / Total interest payments

X_4 = Cumulative profitability = Retained earnings / Total assets

X_5 = Liquidity

X_6 = Capitalization = Equity / Total Capital

X_5 = Size

At the following table, there is a comparison between the two model, Z – score and ZETA – score.

Table 3: Comparison of Z – score 1968 with ZETA – score 1977. (Source: Altman E. [1993], ‘Corporate Finance Distress and Bankruptcy’ p. 2160

Years before	Z – score 1968		ZETA – score 1977	
	Bankrupt (%)	No bankrupt (%)	Bankrupt (%)	No bankrupt (%)
1	93,9	97	96,2	89,7
2	71,9	93,9	84,9	93,1
3	48,3	-	74,5	91,4
4	28,6	-	68,1	89,5
5	36	-	69,8	82,1

This table shows the levels of success for each situation. Analytically, ZETA – score model classifies better the results for bankrupt companies about 5 years ago. On the contrary, the Z – score shows better results in the case of no bankrupt companies.

3.9 Subjective Analysis

The subjective analysis is the traditional way of measuring if the borrower will be able to default. There are some qualitative and quantitative characteristics such as the character, the capacity, the capital, the conditions and the collateral. This analysis is known as the 5C analysis. However, financial institutions examine more characteristics so the result can be more accurate. These details are the previous transaction class, the total loan leverage, the reputation, the earnings volatility, the existence of other collaterals and, finally, the financial situation. Of course, the amount of collective data is differentiated depending on the size of risk exposure and the cost of each information.

CHAPTER 4

Data - Methodology

1. Introduction

The main question to be addressed is the following: Is credit risk related to certain variables that are included in the ordinary accounting statements? In the absence of any information about the credibility of the companies in the sample, we use as surrogate their stock returns. That is, we assume that the higher the credibility of a company the higher its stock performance. As a result, the relationship between stock returns and certain financial ratios is examined.

2. Data

Our sample includes 80 randomly selected companies, which are listed in the Athens Stock Exchange. The time period under consideration includes 8 years, from 2000 to 2007. It is worth to note that 2008 and the following years were excluded because of the economic crisis. That is, in such periods accountings as well as stock exchange variables take extreme values, thus affecting the results of the relevant analysis.

In the period under study, there are two distinct phases of the Athens Stock Exchange: The downwards (from 2000 to 2003) and the upwards (from 2003 to 2007) ones. It is very interesting, therefore to study the efficiency of credit scoring models in these two quite different periods.

For the purposes of the study, the following variables were used:

1. Current assets,
2. Current liabilities,
3. Earnings before interest and taxes,
4. Net income,
5. Common stock closing prices.

3. Methodology

First of all, the return of each company was calculated by using the following equation form:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$$

Where: R = return of stock

$P_{i,t}$ = closing price of i stock, at t time

$P_{i,t-1}$ = closing price of i stock, at t-1 time

Next, three crucial financial ratios were selected, which are historically related to a firm's credibility:

1. Liquidity Ratio,
2. Profitability Ratio and
3. Capital Structure Ratio.

The correlation between the stock performance of each company in the sample and these three ratios was analyzed. In order to focus on the effect of each financial ratio on the stock performance, we used the following procedure:

- ✓ We classified the annual 80 prices of a ratio (one for each company in the sample) into five groups: the first group included the 16 higher prices, the second group included the next 16 prices etc and the fifth group included the 16 lowest prices.
- ✓ We analyzed the relationship between stock performance and the ratio, only for groups A1 and A5. So, if a positive or negative relationship exists, the results will differ substantially for groups A1 and A5.

3.1 Liquidity Ratio

This ratio is commonly used to determine an institution's ability to pay off its short – terms debts obligations. Generally, the higher the value of this ratio, the larger the margin of safety that the institution possesses to cover short – term debts.

The form of equation is:

$$\text{Liquidity Ratio} = \frac{\text{Current Assets}}{\text{Current Liabilities}}$$

After the calculation of liquidity ratio, the data were sorted from highest to lowest and then, they were divided to five equal groups (A1, A2, A3, A4, A5) with sixteen companies in each. As being logical, the first group (A1) has the highest values and the last group (A5) has the minimum values. All the values of ratios were compared with the respectively returns. If the relation is positive, group A1 will have the highest values of liquidity ratio and returns, too. If there is a negative relation, the exact opposite it will happen.

3.2 Profitability Ratio

This ratio shows the ability of business to generate earnings as compared to its expenses and other costs incurred during a specific period of time. This combines the management of liquidity, assets and liabilities. Generally, a higher value relative to the same ratio from a previous period is indicative that the business is doing well.

There are two forms of this ratio:

1. $\text{Return on Equity} = \frac{\text{Net Income available to common}}{\text{Equity}}$

2. $\text{Return on Capital employed} = \frac{\text{Net earnings before interest and taxes}}{\text{Total Assets}}$

Being calculated both profitability ratios, it was followed the exact process as this in liquidity ratio. There were made five equal groups (A1, A2, A3, A4, A5) with sixteen companies and they were classified by highest (A1) to lowest (A5). These values were compared with the returns. So, in a positive relation between of them, the A1 group will have the highest values of ratio and returns and the A5 group will have the lowest ratios and returns, on contrary with a negative situation.

3.3 Capital Structure Ratio

This ratio involves company's long - term debts, short – term debts, common equity and preferred equity. It shows how a firm finances its overall operations and growth by using different sources of funds.

The equation form is:

$$\text{Capital Structure Ratio} = \frac{\text{Total Liabilities}}{\text{Total Assets}}$$

The process was the same with this above on two ratios. There are, also, five groups (A1, A2, A3, A4, A5). The only difference is that there must be a negative connection between capital structure ratio and returns. So, in a positive relation, the A1 group will have high values of capital structure ratio and high returns, as well the A5 group will have the lowest values with low returns. On contrary, in a negative situation, when the ratio is high, the return is lower than that in a previous period.

CHAPTER 5

Analysis of Data and Interpretation of Results

1. Introduction

In this chapter the figures that result from the analysis of our sample are presented and discussed. At the beginning the distributional properties of the three ratios are examined. At a second stage, the following hypotheses of our analysis are tested:

- ✓ Liquidity and profitability are negatively related to credit risk. Therefore, they are negatively related to stock performance as well.
- ✓ Capital structure is positively related to credit risk (the lower the portion of equity the higher the risk of default). Therefore, it is positively related to stock performance.

2. Distributional Properties of the Financial Ratios

In order to understand the characteristics of the distributions of the three financial ratios, we proceeded to calculate their basic statistical characteristics, i.e. the mean, median, standard deviation, kurtosis, skewness, etc.

We have to remind that the statistical description of a distribution can reveal the variability of prices and therefore the magnitude of risk. The number of observations is great enough (>30) and we can tell that the Limit Theory is applied. So, as the size of data tends to infinity, the distribution tends to be normal.

Table 4 presents the average annual price of liquidity ratio the period 2000 to 2007. We consider only groups A1 and A5, which are the groups of companies with the highest values and that of the lowest values (see previous chapter).

In Table 5 the main characteristics of the distribution of current ratio of Table 4 are presented.

Table 4: Liquidity Ratio 2000 - 2007.

LIQUIDITY RATIO			
A1		A5	
2000	4,01	2000	0,44
2001	5,36	2001	0,72
2002	3,51	2002	0,82
2003	3,52	2003	0,73
2004	3,63	2004	0,69
2005	3,44	2005	0,67
2006	3,61	2006	0,67
2007	2,84	2007	0,70

Table 5: Statistical description of Liquidity Ratio.

A1		A5	
Mean	3,75	Mean	0,68
Median	3,57	Median	0,70
Standard Deviation	0,73	Standard Deviation	0,11
Sample Variance	0,53	Sample Variance	0,01
Kurtosis	4,23	Kurtosis	4,31
Skewness	1,70	Skewness	-1,62
Minimum	2,84	Minimum	0,44
Maximum	5,36	Maximum	0,82
Sum	29,96	Sum	5,46

Table 5 reveals that the average liquidity ratio of group A1 is about 6 times as high as the corresponding value of group A5. Therefore, companies in group A1 are quite more liquid than companies in group A5. Given that, liquidity is negatively related to credit risk, we expect to see that companies in the first group will exhibit higher performance than companies in group A5. On the other hand, liquidity in group A1 is more diversified than group A5 as the standard deviation shows ($0,73 > 0,11$). This difference might confuse the results, given that group A1 is not as homogenous as A5.

Regarding kurtosis and skewness, we can note the following:

- In group A1, kurtosis has a price bigger than 3 which is the base for normal distributions. So it can be characterized as leptokurtic. Similar is the case of A5.
- There is a positive skewness to A1 group (data is skewed to right). On the contrary, A5 has a negative skewness, and the data is skewed to the left.

Tables 6 and 8 present the average annual price of profitability ratio the period 2000 to 2007. We take into consideration only groups A1 with highest values and A5 with lowest ones.

In Tables 7 and 9 the main characteristics of the distribution of current ratio of the above tables are presented.

Table 6: Profitability Ratio (1) 2000 - 2007.

PROFITABILITY RATIO (1)			
A1		A5	
2000	0,39	2000	-0,11
2001	0,41	2001	-0,12
2002	0,23	2002	-0,18
2003	0,29	2003	-0,33
2004	0,30	2004	-0,14
2005	0,71	2005	-0,21
2006	0,36	2006	-0,25
2007	0,33	2007	-0,31

Table 7: Statistical description of Profitability Ratio (1).

A1		A5	
Mean	0,38	Mean	-0,20
Median	0,35	Median	-0,19
Standard Deviation	0,15	Standard Deviation	0,08
Sample Variance	0,02	Sample Variance	0,01
Kurtosis	4,60	Kurtosis	-1,43
Skewness	1,94	Skewness	-0,38
Minimum	0,23	Minimum	-0,33
Maximum	0,70	Maximum	-0,11
Sum	3,03	Sum	-1,66

Table 7 reveals that the average profitability ratio of group A1 is about 3 times higher than the corresponding value of group A5. Therefore, companies in group A1 are quite more profitable than companies in group A5. Given that, profitability is negatively related to credit risk, we expect to see that companies in the first group will exhibit higher performance than companies in group A5. On the other hand, profitability in group A1 is more diversified than group A5 as the standard deviation shows ($0,15 > 0,08$). This can confuse the results, given that group A1 is not as homogenous as A5.

Regarding kurtosis and skewness, we can note the following:

- In group A1, kurtosis has a price bigger than 3 which is the base for normal distributions. So it can be characterized as leptokurtic. Similar is the case of A5.
- There is a positive skewness to A1 group (data is skewed to right). On the contrary, A5 has a negative skewness, and the data is skewed to the left.

Table 8 uses data of capital employed ratio.

Table 8: Profitability Ratio (2) 2000 - 2007.

PROFITABILITY RATIO (2)			
A1		A5	
2000	0,13	2000	-0,01
2001	0,10	2001	-0,03
2002	0,14	2002	-0,10
2003	0,12	2003	-0,08
2004	0,04	2004	0,00
2005	0,04	2005	0,00
2006	0,03	2006	0,00
2007	0,04	2007	0,00

Table 9: Statistical description of Profitability Ratio (2).

A1		A5	
Mean	0,08	Mean	-0,03
Median	0,07	Median	-0,01
Standard Deviation	0,05	Standard Deviation	0,04
Sample Variance	0,01	Sample Variance	0,00
Kurtosis	-2,32	Kurtosis	-0,10
Skewness	0,19	Skewness	-1,28
Minimum	0,03	Minimum	-0,10
Maximum	0,14	Maximum	0,00
Sum	0,65	Sum	-0,22

Table 9 reveals that the average profitability ratio of group A1 is a bit higher than the corresponding value of group A5. Therefore, companies in group A1 are quite more profitable than companies in group A5. Given that, profitability is negatively related to credit risk, we expect to see that companies in the first group will exhibit higher performance than companies in group A5. On the other hand, profitability in group

A1 is diversified similar with that in group A5 as the standard deviation shows (0,05 ~ 0,04).

Regarding kurtosis and skewness, we can note the following :

- In group A1 and A5, kurtosis has a price shorter than 3 which is the base for normal distributions. So it can be characterized as platycurtic and all the marks are concentrated toward the mean.
- There is a positive skewness to A1 group (data is skewed to right). On the contrary, A5 has a negative skewness, and the data is skewed to the left.

Table 10 presents the average annual price of capital structure ratio the period 2000 to 2007. We consider, again, only groups A1 and A5.

In Table 11 the main characteristics of the distribution of current ratio of Table 10 are presented.

Table 10: Capital Structure Ratio 2000 - 2007.

CAPITAL STRUCTURE RATIO			
A1		A5	
2000	0,87	2000	0,06
2001	1,07	2001	0,12
2002	1,81	2002	0,11
2003	1,72	2003	0,09
2004	0,48	2004	0,00
2005	0,51	2005	0,00
2006	0,54	2006	0,00
2007	0,56	2007	0,00

Table 11: Statistical description of Capital Structure Ratio.

A1		A5	
Mean	0,94	Mean	0,05
Median	0,72	Median	0,03
Standard Deviation	0,54	Standard Deviation	0,05
Sample Variance	0,30	Sample Variance	0,00
Kurtosis	-0,84	Kurtosis	-2,12
Skewness	0,94	Skewness	0,37
Minimum	0,48	Minimum	0,00
Maximum	1,80	Maximum	0,12
Sum	7,56	Sum	0,38

Table 11 reveals that the average capital structure ratio of group A1 is about 7 times higher than the corresponding value of group A5. Therefore, companies in group A1 have preserved greater capital than companies in group A5. Given that, this ratio is positively related to credit risk, we expect to see that companies in the first group will exhibit lower performance than companies in group A5. On the other hand, capital structure in group A1 is more diversified than group A5 as the standard deviation shows ($0,54 > 0,05$). This difference might confuse the results, given that group A1 is not as homogenous as A5.

Regarding kurtosis and skewness, we can note the following :

- In group A1 and A5, kurtosis has negative prices and lower than 3 which is the base for normal distributions. So it can be characterized as platycurtic and the data is concentrated toward the mean.
- There is a positive skewness for both groups, A1 and A5, so data is skewed to right.

3. The Effect of Liquidity Ratio on Stock Returns

Table 12 shows the relationship between liquidity ratio and stock returns. For group A1, the value of the ratio is fluctuated from 5,40 to 2,84 while returns range from 1,55 to -0,14. On the other hand, the corresponding ratio values for group A5 are between 0,83 to 0,44 and the returns range from 1,64 to -0,18 .

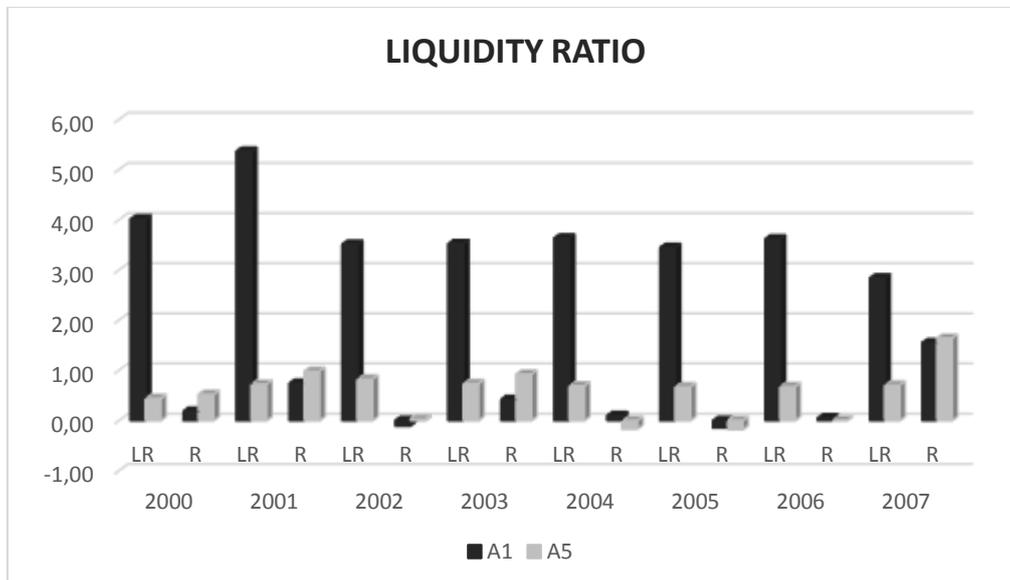
The above figures clearly suggest that our hypothesis should be rejected, given that the market did not consider companies with high liquidity ratio as more safe. On the contrary, in five out of eight years, companies with low liquidity ratios performed quite better than their high liquidity ratios counterparts.

We reach the same conclusion by observing Chart 3, which clearly states that there is no positive correlation between the liquidity ratio and stock returns. For example, in the period 2000 - 2003, the ratio had had negative relationship to returns, while in the period 2004 - 2007 the opposite was true.

Table 12: Data of Liquidity Ratio and Returns by 2000 to 2007.

LIQUIDITY RATIO					
A1			A5		
	LR	R		LR	R
2000	4,01	0,18	2000	0,44	0,52
2001	5,36	0,74	2001	0,72	0,98
2002	3,51	-0,11	2002	0,83	0,03
2003	3,52	0,42	2003	0,74	0,92
2004	3,63	0,10	2004	0,69	-0,17
2005	3,45	-0,14	2005	0,67	-0,18
2006	3,62	0,05	2006	0,68	0,01
2007	2,84	1,55	2007	0,70	1,64

Chart 3: Liquidity ratio versus Stock Returns chart.



4. The Effect of Profitability Ratio on Stock Returns

Table 13 shows the relationship between profitability ratio and stock returns. For group A1, the value of the ratio is fluctuated from 0,71 to 0,23 while returns range from 2,27 to -0,08. On the other hand, the corresponding ratio values for group A5 are between -0,11 to 0,33 and the returns range from 2,36 to -0,10 .

The above results clearly suggest that our hypothesis should be rejected, given that the market did not consider companies with high profitability ratio as more safe to invest. On the contrary, in only four out of eight years, companies with high profitability ratio performed quite better than their low profitability ratio counterparts.

We reach the same conclusion by observing Chart 4, which clearly states that there is no positive correlation between the profitability ratio and stock returns. For example, in the period 2000 - 2002, in general, the ratio had positive relationship to returns, while in the period 2004 - 2007 the opposite was true.

Table 13: Data of Profitability Ratio (1) and Returns by 2000 to 2007.

PROFITABILITY RATIO (1)					
A1			A5		
	PR(1)	R		PR(1)	R
2000	0,39	0,32	2000	-0,11	0,30
2001	0,42	0,75	2001	-0,12	1,11
2002	0,23	-0,08	2002	-0,18	0,00
2003	0,29	0,71	2003	-0,33	1,11
2004	0,30	-0,08	2004	-0,14	-0,01
2005	0,71	-0,16	2005	-0,21	-0,10
2006	0,36	-0,11	2006	-0,25	0,12
2007	0,33	2,26	2007	-0,31	2,36

Chart 4: Profitability Ratio (1) versus Stock Returns chart.

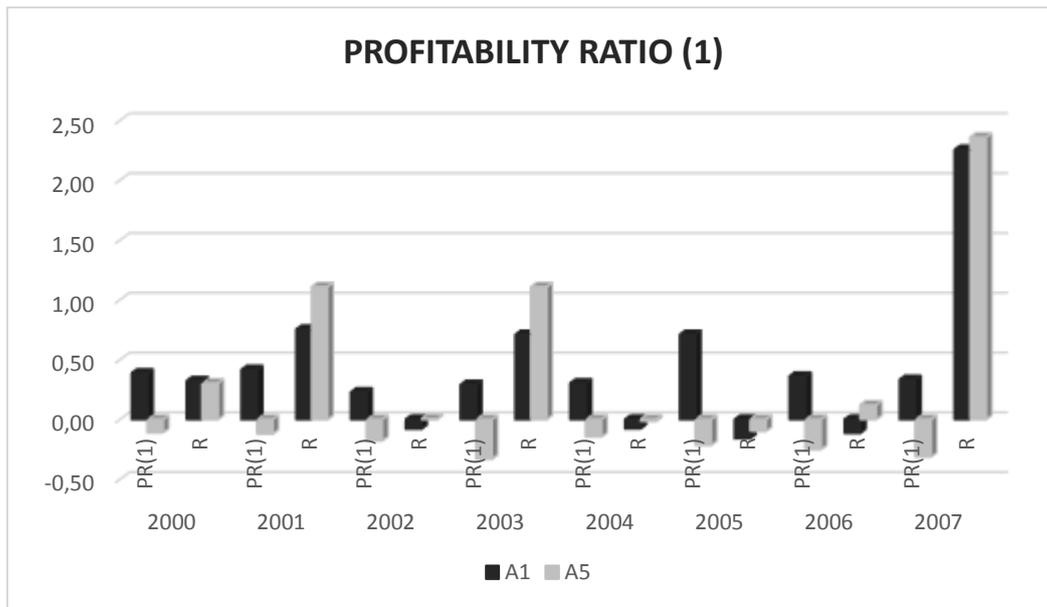


Table 14 shows, again, the relationship between profitability ratio and stock returns. For group A1, the value of the ratio is fluctuated from 0,14 to 0,03 while returns range from 1,24 to -0,05. On the other hand, the corresponding ratio values for group A5 are between -0,01 to 0,00 and the returns range from 2,28 to -0,29 .

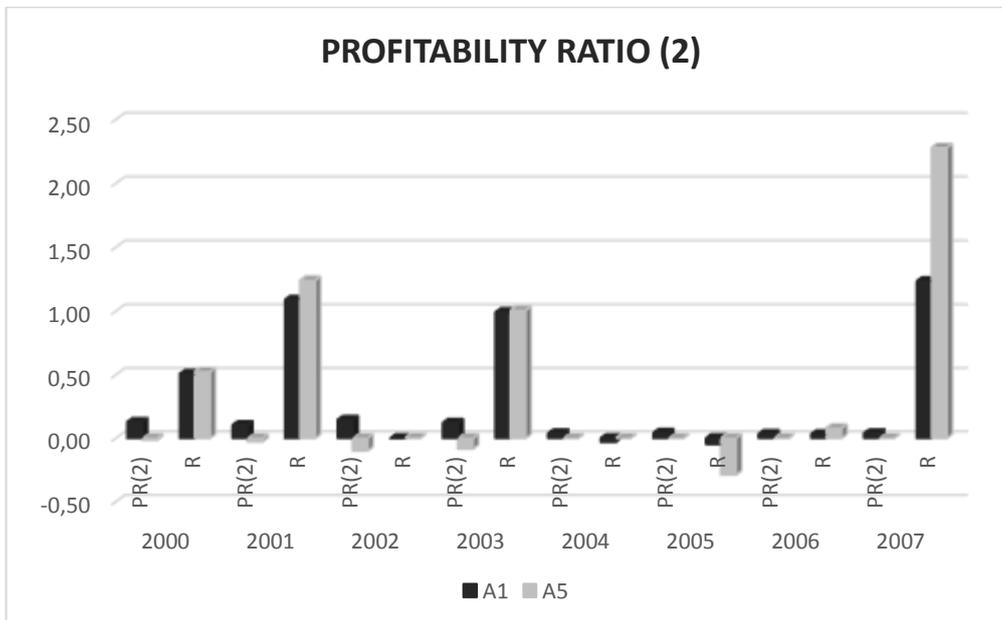
The above results clearly suggest that our hypothesis should be rejected, given that the market did not consider companies with high profitability ratio as more safe to invest. On the contrary, in almost two out of eight years, companies with high profitability ratio performed quite better than their low profitability ratio counterparts.

We reach the same conclusion by observing Chart 5, which clearly states that there is no positive correlation between the profitability ratio and stock returns. For example, only in years 2002 and 2005 the ratio had had positive relationship to returns, while in the remaining years the opposite was true.

Table 14: Data of Profitability Ratio (2) and Returns by 2000 to 2007.

PROFITABILITY RATIO (2)					
A1			A5		
	PR(2)	R		PR(2)	R
2000	0,13	0,51	2000	-0,01	0,52
2001	0,10	1,09	2001	-0,03	1,24
2002	0,14	-0,00	2002	-0,10	0,00
2003	0,12	0,99	2003	-0,08	1,01
2004	0,04	-0,03	2004	0,00	0,00
2005	0,04	-0,05	2005	0,00	-0,29
2006	0,03	0,03	2006	0,00	0,08
2007	0,04	1,24	2007	0,00	2,28

Chart 5: Profitability Ratio (2) versus Stock Returns chart.



5. The Effect of Capital Structure Ratio on Stock Returns

Finally, Table 15 shows the relationship between capital structure ratio and stock returns. For group A1, the value of the ratio is fluctuated from 1,81 to 0,48 while returns range from 1,31 to -0,05. On the other hand, the corresponding ratio values for group A5 are between 0,12 to 0,00 and the returns range from 2,28 to -0,29 .

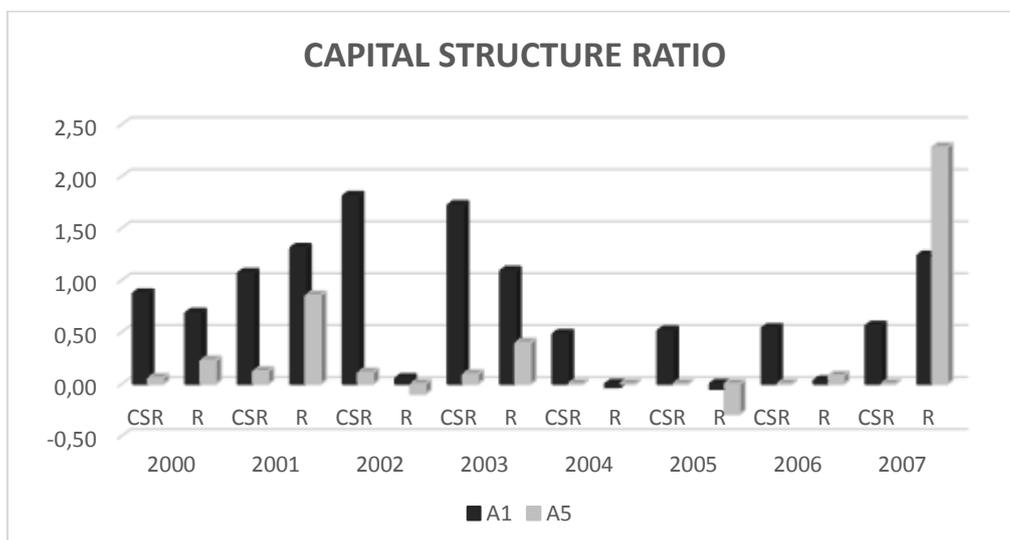
The above results clearly suggest that our hypothesis should be rejected, given that the market did not consider companies with low capital preservation as more safe to invest. On the contrary, only in last two out of eight years, companies with a high capital structure ratio performed quite better than their low ones ratio counterparts.

We reach the same conclusion by observing Chart 6, which clearly states that there is no positive correlation between this specific ratio and stock returns. For example, only in years 2006 - 2007 the ratio had had positive relationship to returns, while in the remaining years the opposite was true.

Table 15: Data of Capital Structure Ratio and Returns by 2000 to 2007.

CAPITAL STRUCTURE RATIO					
A1			A5		
	CSR	R		CSR	R
2000	0,87	0,68	2000	0,06	0,23
2001	1,07	1,31	2001	0,12	0,85
2002	1,81	0,05	2002	0,11	-0,09
2003	1,72	1,09	2003	0,09	0,39
2004	0,48	-0,03	2004	0,00	0,00
2005	0,51	-0,05	2005	0,00	-0,29
2006	0,54	0,03	2006	0,00	0,08
2007	0,56	1,23	2007	0,00	2,28

Chart 6: Capital Structure Ratio versus Stock Returns chart.



More analytically, the main conclusion of this study is that there is no connection between ratios and returns of stocks either examining the whole period either parts of this exact period, 2000 to 2007. There is no specific pattern between them as there are companies with losses and very high returns, or the opposite, something not compatible. The logical thing could be, if the closing price of any stock increases, its return will be greater than before. Considering the findings, we are not capable to estimate the behavior of each stock according to these financial ratios (increasing pattern or decreasing one). So, it is clearly that, none of these ratios could be considered as appropriate to make credit scores. Moreover, financial theory recommends that only systematic risk affects the stock' returns and not credit risk. By concluding, a new rating system could not be able to build.

CHAPTER 6

Summary and Conclusions

Credit risk is the most crucial risk. Given that cash transactions are very rare, almost all companies face this kind of risk, which is crucial especially for banks, which have huge numbers of customers, ranging from privates to enterprises. Within the framework of the present study, we have attempted to analyze the parameters which comprise credit risk, as well as to record the several methodologies which have been developed in order to measure and manage this kind of risk, focusing on the credit score systems which have been suggested and tested in the relevant literature. We have also stressed on the European rules towards the elimination of the consequences of credit risk in the banking sector (Basel II).

Finally, we have tested certain hypotheses about the correlation of credit risk and the three important accounting parameters, named liquidity, profitability and capital structure. Our sample includes 80 companies, listed in the Athens Stock Exchange. Surprisingly, the results of our analysis suggest that the above parameters are not related to credit risk. There is no chance to estimate the probability of default or the behavior of a stock by calculating the specific three ratios. So, none of the above parameters could be considered as appropriate to participate in a credit scoring system.

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